2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) | 978-1-7281-8028-1/20/$31.00 ©2021 IEEE | DOI: 10.1109/IAEAC50856.2021.9390626

Overview of image colorization and its applications

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***Abstract*—Image colorization is a computer-assisted technology to colorize grayscale images. With the rapid development of information technology and increasing image data, the study of image colorization has also become particularly important. Through the summary and analysis of related literature in recent years, the paper presents a review about the techniques of image colorization. In addition, we also divide image colorization methods into three categories, then describe their representative methods and applications, and discuss their advantages and limitations in future development trends. The results show specially that model based colorization has a better colorization effect than other methods, whether in terms of image quality or real-time performance.**

Keywords—image colorization, reference image, colorization matrix, model function, colorization applications

I. INTRODUCTION

Image colorization is the process of adding color information to grayscale images with the aid of computer, which has an important influence on human perception of visual information [1]. This technique was also used to process the moon images brought back by the "Apollo" landing on the moon. In the early colorization process with artist intervention, it took time-consuming segmentation and then colorization. After that, with the development of new technologies, colorization is applied to various fields. For example, In the field of film and television, the colorization is used to automatically add color to photos or videos to give the audience a comfortable visual experience. In the medical field, colorization can colorize some important medical gray-scale images to assist doctors in making professional judgments [2,3]. Most importantly, colorization can also be applied to the field of image compression. It can get better results than the JPEG [4], which may incur blocking effects and blurred image in the case of high compression ratio.

With the advance of the research of image colorization technology, a variety of literature have proposed the colorization methods, which vary substantially. Given the user's participation in problem solving and the way of searching for data, numerous papers categorize colorization methods. For example, Žege et al. divided image colorization into scribble-based, example-based and deep learning methods [3]. However, based on the source of chrominance information needed for colorization, this paper remarks the image colorization in terms of colorization based on reference image, colorization matrix, and model function.

In this paper, reference image based colorization and its application in color correction are given in Section II. colorization matrix based colorization and its application in image coding are introduced in Section III. Model based colorization and its application in image coding are described in Section IV. Different comparative analysis of three methods is discussed in Section V, and conclusions are drawn in Section VI.

II. REFERENCE IMAGE BASED COLORIZATION

In order to reduce the influence of manual intervention on the colorization process, colorization based on reference image is proposed. It is also called color transfer technology between images. Initially, Reinhard [5] applied this method to the field of image colorization. Based on appropriate reference image color features, they transferred these similar color information to the target image. Then Welsh et al. [6] proposed the colorization algorithm based on this. They used luminance and texture information as pixel matching features to achieve the spread of chrominance information. This method of colorization result is shown in Fig. 1. However, the colorization effect depends on the correlation between the texture and grayscale distribution of the reference image and the target image. If the correlation is poor, the colorization effect is also poor.

a) reference image b) target image c) colorized image

Fig. 1. Colorization reference method by Welsh et al. [6]

Furthermore, Irony et al. introduced image segmentation method, as shown in Fig. 2. They used the K-Nearest-Neighbor (KNN) algorithm to classify the pixels of the reference image and find the best matching area, then transfer the color to the relevant pixels with higher confidence [3,7]. In the study [8], the probabilistic segmentation is adopted to solve the regional color spread of reference image to target image. However, accurate image segmentation remains a problem. Therefore, more and more researches have focused on the impact of local features on color transfer, and some solutions have been proposed. Reference [9] used the simple linear iterative cluster (SLIC) segmentation algorithm to divide the reference image into a series of superpixels, and select the best matching superpixels to transfer chrominance information. In addition, there are also models for color transfer, but they all involve a series of complicated steps.

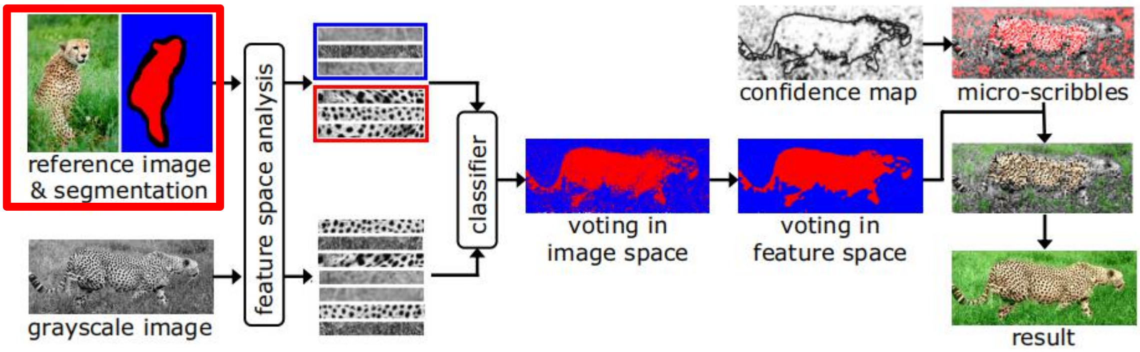

Fig. 2. Segmentation and reference based colorization by Irony et al. [7]

The advantage of the colorization method based on the reference image is simple. There is no need for human intervention once the reference image is selected. Besides, it has a better colorization effect on the single color image. However, the selection of similar texture characteristics of the reference image and grayscale image is a difficult task. Since image segmentation is introduced, the complexity of colorization is increased accordingly, and there are problems such as time-consuming and color mis-diffusion.

Apart from the above discussion, reference image based colorization can also be used for color correction. Reference [5] adopted this method to transfer the color characteristics of the reference image to target image through statistical analysis. It can make the overall color of the target image similar to the reference image, which completes the color correction of the target image. Furthermore, based on the average difference of color channel of the target and reference image, we can change the color distribution in the target image to achieve a better color correction effect.

III. Colorization Matrix Based Colorization

The earliest colorization method is completely manual. People need to segment the image first, and then assign the desired color to each image block. This method requires numerous manual intervention with low efficiency and is time-consuming. Thus, colorization based on colorization matrix is proposed with less manual intervention.

The linear combination of several column vectors of the colorization matrix can represent the colorization process, which determines the performance of colorization-based coding [10]. Levin et al. regarded colorization as a global optimization problem based on the following premise: neighboring pixels with similar luminance have similar chrominance information [11]. Levin et al. defined the quadratic cost function to solve the optimization problem as follows,

$$J(\boldsymbol{u}) = \|\boldsymbol{x} - \boldsymbol{A}\boldsymbol{u}\|, \boldsymbol{A} = \boldsymbol{I} - \boldsymbol{W} \tag{1}$$

where **I** is an $n \times n$ identity matrix, n is the total number of pixels, **W** is the sparse matrix of $n \times n$, corresponding to the luminance similarity weight between the pixel and its neighboring pixels, **x** contains the chrominance component of representative pixels (RPs), **u** is the solution of chrominance information. Then the minimization of (1) can be reduced to

$$\boldsymbol{u} = \boldsymbol{C}\boldsymbol{x}, \boldsymbol{C} = \boldsymbol{A}^{-1} \tag{2}$$

The matrix **C** is called the levin colorization matrix, and depends on the weight of the defined luminance similarity. Based on the above, different colorization matrices are proposed to reconstruct images. Lee et al. proposed a method to construct a colorization matrix based on luminance images with multi-scale meanshift segmentation [12,13]. The colorization matrix can recover chrominance information in (2), which consists of less column vectors, as well as representative pixels [14].

In order to obtain chrominance image with fewer representative pixels. Reference [14] used the colorization method of representative graph spectrum (RGS) based on the graph Fourier transform as shown in Fig. 3. The proposed colorization matrix is constructed with the graph spectrum, which can restore chrominance information in (2) and achieve better performance.

The limitations of colorization method based on colorization matrix is that it can only approximate the color components effectively. If the matrix structure is not suitable, there exists blur and diffusion of the image boundary color. For images with complex textures, it needs to be carefully designed. However, the advantage of colorization matrix is global optimized without the explicit segmentation. Users can freely choose colorization area. Then chrominance information can be spread to the whole image.

Apart from the above discussion, colorization matrix can also be used for image coding. Generally, in colorization-based coding, the image can be compressed by extracting the RPs and coding of the grayscale edition of the original image. The RPs mainly store the spatial position of pixels and the corresponding chrominance information. In the decoding stage, the colorization algorithm uses the matrix to get all pixel values. For example, Reference [13,14] based on this obtain higher compression ratio and quality images than the JPEG.

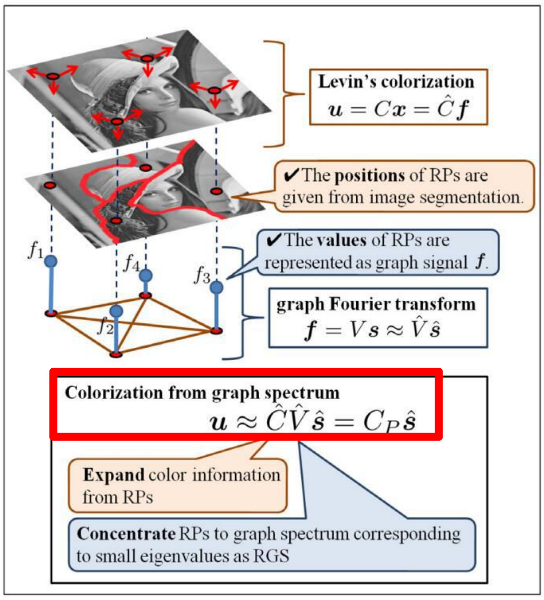

Fig. 3. Structure of colorization based on the graph Fourier transform [14].

IV. Model Based Colorization

With the availability of massive data on the Internet, machine learning and deep learning have been successfully applied to image colorization. They can essentially be understood as fitting a large amount of data to form a functional relationship. The colorization model based on this implements the mapping process from grayscale input to chrominance output, which is based on the assumption that adjacent pixels with similar luminance or texture features have similar chrominance information. Many scholars mostly use models to learn the mapping function. Reference [15] proposed a prediction method based on supervised learning with Laplacian-regularized least squares (LapRLS). The model can predict the chrominance values by inputting pixel positions and luminance.

However, nowadays diverse and complex images require superior colorization technology. Deep learning models are more and more commonly used in image colorization. The colorization process based on deep learning [16] contains two stages: training and colorization. After the model is trained on numerous different types of color images, the loss function can be minimized. Then the image can be restored through the function mapping relationship based on the optimal model.

Some scholars use deep learning to perform automatic or semi-automatic colorization and achieve good performance. Based on some databases, Cheng et al. first proposed an algorithm for colorizing grayscale images automatically using deep neural networks (DNN). The proposed network extracts features from numerous gray-scale images to be colored. The network includes one input layer, three hidden layers and one output layer as shown in Fig. 4. The connection of each pair of neurons refers to the weights learned in the image database [17]. With the DNN trained, the corresponding pixel chrominance can be output, combining bilateral filtering to improve the result.

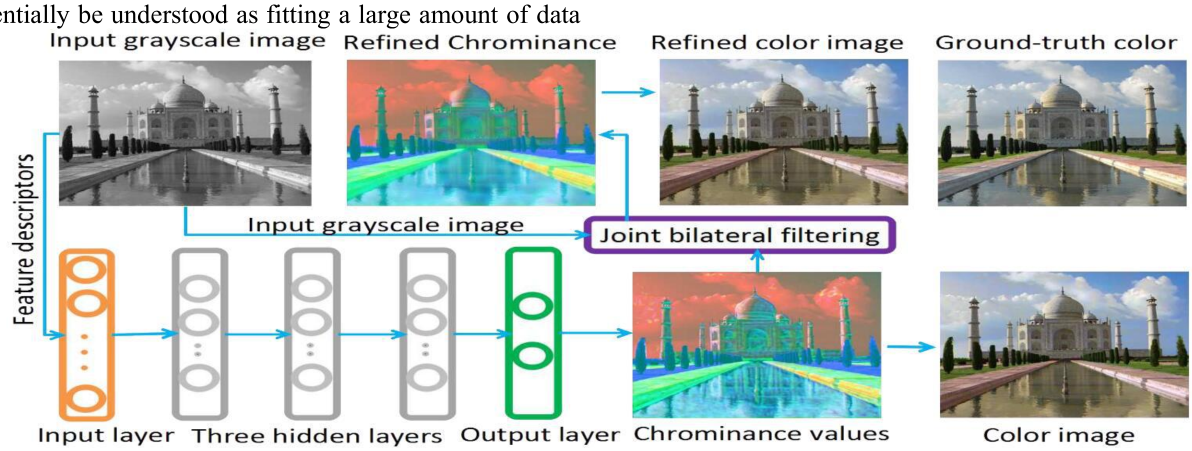

Fig. 4. Architecture of the proposed DNN [17]

However, due to adoption of simple network structure, the training data is relatively small, which limits the colorization effect to some extent. In the study [18], an automatic colorization technology was proposed with convolutional neural networks (CNN), which combines global and local features. The proposed network main contains a low-level, mid-level and global feature network [18]. The special feature of the network structure is that the global features are used to guide the local features while performing colorization, which avoids large deviations in colorization effect. In addition, the network can predict the corresponding color channels according to the luminance channel of the image in the L*a*b* color space. In an end-to-end manner, the model is trained on a large dataset, which can be used for scene recognition, with joint coloring and classification loss [18]. Nevertheless, the colorization effect is better for scenes of specific colors, but not for some images with multiple colors.

Deep learning mainly focuses on supervised discriminant models, but it also has great significance for semi-supervised or unsupervised generative models. Inspired by game theory in 2014, Ian Goodfellow proposed the Generative Adversarial Networks (GANs) [19] that is widely used for colorization. The GAN adopts two networks to confront each other, directly learn the true distribution mapping of the sample. Therefore, the images colorized by it are of high quality.

In the study [20], a novel technology is proposed with unsupervised diverse colorization. In the proposed GAN as shown in Fig. 5, after the input of the conditional gray image, the generator G will pass through a convolutional network with a step size of 1, and generate a three-channel color image. And the discriminator D is used to discriminate the real images and the fake images. Furthermore, in order to achieve various colorization outputs, the generator needs to introduce noise channels. In colorization process, the chrominance channels can be predicted by the model and then combined with the grayscale channel to obtain color image.

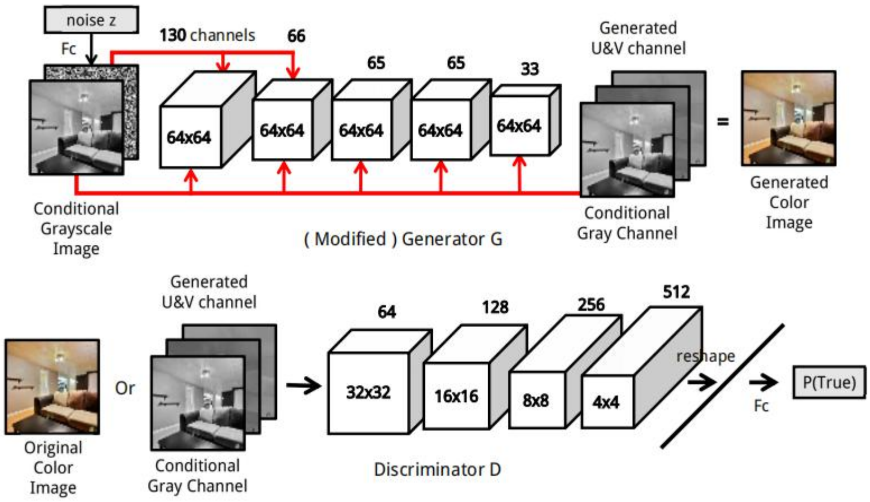

Fig. 5. Architecture of the proposed GAN [20]

The most prominent advantage based on colorization model is that the established model can approximate any function as much as possible. The model can automatically realize the mapping relationship from luminance to chrominance. For example, the neural network model can extract the features of high-level semantic information in the image with a stronger generalization ability, which can colorize various types of gray images. However, the training of the network is not easy to converge, which may cause contextual confusion and edge color mixing.

In terms of application, model based colorization can also be used for image coding. The principle is similar to the colorization matrix mentioned above. For example, Reference [21] proposes a low-cost colorization for image compression with the deep tree-structured network model that achieves a better result than the JPEG. In the context of big data, image compression based on model will be more widely used and developed.

V. Comparative Analysis

Gray-scale image colorization technology has always been a hot research topic. The traditional colorization method is based on reference image and colorization matrix. However, in the face of a large number of image data, it is the model that is used to solve the image colorization problem. In order to show the comparison of traditional methods and mode method more intuitively, the target image, reference image and colorization method results are shown in Fig. 6 [17]. Obviously, the Peak Signal-to-Noise Ratio (PSNR) based on the model is higher than reference image. This also shows model-based colorization has higher efficiency and better effect.

20dB

a) target image b) reference image c) Welsh et al. [6]

21dB d) Irony et al. [7] | 22dB e) Gupta et al. [9] | 33dB f) Cheng et al. [17]

Fig. 6. PSNR comparison of colorization methods. c)-e) used the colorization based on reference image. f) used the colorization based on model.

Besides, the colorization methods based on reference image and colorization matrix require manual intervention, which consume lots of time and energy, and cause unstable colorization effect. As the size of images increases, the colorization speed decreases markedly. Obviously, in the era of artificial intelligence, this method is no longer suitable for more efficient image colorization. The model uses large-scale data to train the network, which avoids manual intervention and achieves a very good effect. Although the model complexity is increased, it can get a better mapping effect. However, the state-of-the-art methods are still far from being applied to critical real-world scenarios [22].

VI. CONCLUSIONS

In this paper, we summarize and remark the methods of colorization. The colorization process and its applications of every method is described, and the advantages and disadvantages are discussed. Compared with other colorization methods, the model colorization effect is significant. Driven by novel technology in the future, Image colorization will develop in the direction of unsupervised learning to achieve high-quality reconstructed images. If possible, combining with new technologies, using diversified colorization and multiple data sets may achieve a better colorization effect and broader application scenarios.

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